EEP55C30-202324 ALGORITHMS FOR QUANTUM COMPUTING

Project Proposal

Lingyu Gong

23337765

November 30, 2023

Comparison of different neural network models in quantum machine learning performance

1 Background

Quantum Neural Networks (QNNs)[1] leverage quantum computing to enhance machine learning. These networks operate with quantum bits and leverage quantum gates to process inputs, seeking to harness the computational parallelism and interconnectedness of quantum states. By integrating elements like quantum superposition and entanglement, QNNs aim to handle large-scale data sets and complex computations more effectively than their classical counterparts. They consist of layers of quantum perceptron—quantum analogs to classical neurons—and have the potential to significantly speed up learning tasks and expand computational capacities in machine learning.

Quantum Convolutional Neural Networks (QCNNs) [2] are a quantum-based counterpart to classical convolutional networks, designed primarily for analyzing patterns in data that is quantum in nature. Utilizing layers of quantum circuits, QCNNs execute convolution and pooling processes akin to their classical counterparts, thereby enabling the extraction of patterns from quantum information. By harnessing the unique aspects of quantum mechanics, such as the superposition of states and quantum entanglement, QCNNs have the potential to outperform traditional networks by efficiently handling tasks that are inherently quantum or that could benefit from the computational acceleration offered by quantum algorithms.

Recurrent Quantum Neural Networks (RQNNs) [3] integrate the principles of quantum computing with the structure of classical recurrent neural networks (RNNs). RQNNs are designed to handle sequential data, leveraging the computational advantages of quantum mechanics. These networks use quantum states and operations to process information over time, potentially offering enhanced efficiency and capacity for tasks involving sequences. RQNNs aim to overcome certain limitations of classical RNNs, such as the vanishing gradient problem, by utilizing quantum properties like superposition and entanglement in their recurrent architecture.

2 Problem

The current exploration of the application of quantum neural networks in machine learning is endless and is a hot topic. Currently, more literature is related to the introduction of quantum computing, the analysis of the application scenarios and the future outlook, etc., or the analysis of the specific implementation of one kind of network, but there are not a lot of articles that conduct comparative analysis.

At this stage, we can already apply the concept of quantum to the classical machine learning neural networks, I then derived the following questions: what is the difference between them? What is the performance? What are the evaluation metrics?

So hopefully, over the next six months, I'll be able to successfully replicate three (and possibly more) common quantum neural networks and perform a comparative analysis to draw conclusions, and hopefully derive some ideas for optimizing the networks.

3 Main objectives

1. Successful replication of three common neural networks
2. Learning how to make assessment comparisons
3. Derive the results of the final comparison, e.g., speed, energy consumption, etc.
4. Try to get innovative ideas

4 Methodology/ Plan

1. Read more information, the first category involves finding quantum neural networks that people have successfully implemented in the last 5 years and analyzing their architectures. The second category is the need to find articles about comparative analysis for reference.

2. With the help of comparative evaluation methods from classical machine learning-related literature, try to see if you can evaluate them with the same ideas.
3. Read while reproducing the network structure, record the result.

5 Main results expected

1. Successfully reproduced quantum neural network models
2. Presenting Evaluation Comparison Data

6 References

[1] K. Beer *et al.*, 'Training deep quantum neural networks', *Nat Commun*, vol. 11, no. 1, p. 808, Feb. 2020, doi: 10.1038/s41467-020-14454-2.

[2] I. Cong, S. Choi, and M. D. Lukin, 'Quantum convolutional neural networks', *Nat. Phys.*, vol. 15, no. 12, pp. 1273–1278, Dec. 2019, doi: 10.1038/s41567-019-0648-8.

[3] J. Bausch, 'Recurrent Quantum Neural Networks'.